

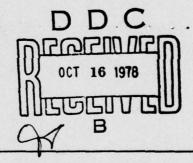


TECHNICAL REPORT ARBRL-TR-02101

SOME BOUNDS FOR OPTIMAL MANEUVERS AND PREDICTORS

Harry L. Reed, Jr.

September 1978





US ARMY ARMAMENT RESEARCH AND DEVELOPMENT COMMAND
BALLISTIC RESEARCH LABORATORY
ABERDEEN PROVING GROUND, MARYLAND

Approved for public release; distribution unlimited.

Destroy this report when it is no longer needed. Do not return it to the originator.

Secondary distribution of this report by originating or sponsoring activity is prohibited.

Additional copies of this report may be obtained from the National Technical Information Service, U.S. Department of Commerce, Springfield, Virginia 22161.

The findings in this report are not to be construed as an official Department of the Army position, unless so designated by other authorized documents.

The use of trade names or manufacturers' names in this report does not constitute indorsement of any commercial product.

UNCLASSIFIED
SECURITY CLASSIFICATION OF THIS PAGE (When Date Entered)

REPORT DOCUMENTATION PAGE	READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER 2. GOVT ACCESSION NO	. 3. RECIPIENT'S CATALOG NUMBER
TECHNICAL REPORT, WRBRL-TR-02101	
A. TITLE (and Subtitie)	5. TYPE OF REPORT & PERIOD COVERED
SOME BOUNDS FOR OPTIMAL MANEUVERS	
AND PREDICTORS.	6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s)	8. CONTRACT OR GRANT NUMBER(#)
Harry L. Reed, Jr	
9. PERFORMING ORGANIZATION NAME AND ADDRESS	10. PROGRAM ELEMENT, PROJECT, TASK
US Army Ballistic Research Laboratory	10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
(ATTN: DRDAR-BLB)	RDTE Project /1L162618AH80
Aberdeen Proving Ground, MD 21005	The second secon
US Army Armament Research & Development Command	SEPTEMBER 1978
US Army Ballistic Research Laboratory	19. NUMBER OF PAGES
(ATTN: DRDAR-BL) Aberdeen Proving Ground MD 21005 14. MONITORING AGENCY NAME & ADDRESS(If different from Controlling Office)	15. SECURITY CLASS. (of this report)
MONITORING AGENCY NAME & ADDRESQUE ALLGRANT TOOL CONTOURING OTICES	is. security ceass. (or and report)
(12)32p.	UNCLASSIFIED
	154. DECLASSIFICATION/DOWNGRADING
16. DISTRIBUTION STATEMENT (of this Report)	
(18) SRIE/U	JAD-E430 111
Approved for public release; distribution unlimi	ted.
17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, If different fr	om Report)
18. SUPPLEMENTARY NOTES	
19. KEY WORDS (Continue on reverse side if necessary and identify by block number	r)
Fire Control Predictors	
Optimum Maneuvers	
Hit Probability	
20. ABSTRACT (Continue on reverse side if necessary and identify by block number	
A problem of some interest in the understand	
is the following pure prediction problem. Given tories \overline{X} for which	the class of target trajec-
20 [1] [1] [1] [1] [2] [2] [2] [2] [2] [2] [2] [2] [2] [2	
$\lim_{B \to \infty} \frac{1}{2B} \int_{-B}^{B} [\ddot{x}(t)]^{2} dt = a^{2} \text{where}$	$x \in \overline{X}$
$B \rightarrow \infty$ 2B J_{-B} in(c), as a whole	-
and the class of predictors P which satisfy the c	ausal principle, find

DD 1 JAN 73 1473 EDITION OF 1 NOV 65 IS OBSOLETE

UNCLASSIFIED
SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

393 471

LB

SECURITY CLASSIFICATION OF THIS PAGE(When Data Entered)

 $\varepsilon_1 = \sup_{X \in \overline{X}} \inf_{P \in P} \varepsilon$

and

$$\varepsilon_2 = \inf_{p \in P} \sup_{x \in \overline{X}} \varepsilon$$

where

$$\varepsilon_2 = \frac{1}{2B} \int_{-B}^{B} [x(t+T) - y(t+T)]^2 dt$$

and y(t+T) is the predicted value of x(t+T) based on values of $x(t-\tau)$ with $\tau \ge 0$.

It is shown that

$$\varepsilon_1 = \varepsilon_2$$

for general N. For the particular value of N=2 which corresponds to a limited acceleration for the target, we have

$$\varepsilon_1 = \varepsilon_2 = \frac{2}{(\lambda T)^2} [\frac{1}{2}aT^2] \approx 0.569 [\frac{1}{2}aT^2]$$

where λ is determined from the solution of an eigenvalue problem for a fourth-order differential equation.

The prediction algorithm p_{α} for which

$$\varepsilon_1 = \varepsilon(x_{\alpha}, p_{\alpha})$$

is a linear operator and the optimal subclass of maneuvers \boldsymbol{x}_{α} is based on a second-order correlation function

$$E[\ddot{x}(t)\ddot{x}(t+\tau)] = \int_0^\infty \alpha(s)\alpha(s+\tau)ds.$$

For the particular case of N=2 we have

$$\alpha(s) = \frac{a}{\sqrt{T}} \left[\frac{\cosh \lambda(s - T/2)}{\cosh(\lambda T/2)} - \frac{\sin \lambda(s - T/2)}{\sin \lambda T/2} \right]$$

for

$$0 \le s \le T$$

and

$$\alpha(s) = 0$$
 otherwise.

No restrictions were placed on \overline{X} and P other than those stated above (i.e., \overline{X} was not restricted to stationary processes and P was not restricted to linear operators).

It is further shown that the strategies given above are good approximations for the more general analysis in which hit probability is the performance measure. This is the case at least for "first cut" analyses.

Bounds such as this help avoid the expenditure of resources to achieve the impossible or to achieve marginally small improvements in fire control design.

TABLE OF CONTENTS

1.	INTRODUCTION																5
2.	LOWER BOUND																7
3.	UPPER BOUND .										•						10
4.	THE EIGENVALU	JE PRO	BLE	М	•												14
5.	THE GENERAL F	PROBLE	EM .														17
6.	THE ALGORITHM	1 po								•							18
7.	CONCLUSIONS .																20
	APPENDIX A .																21
	APPENDIX B .						•				•						23
	APPENDIX C .								•				•				27
	DISTRIBUTION	LIST												•.	:		31

NTIS		White	Sec	tion 🕻
DDC		Buff	Secti	on C
UNANN	DUNCED			Γ.
JUSTIFI	CATION			
BY				
BISTRI	BUTION/A			
				CODES SPLCIA
BISTRI				

1. INTRODUCTION

The goal of this paper is to give some insights into how well a fire control system can be expected to perform with noiseless information and how well a target can avoid being hit with limits on its ability to maneuver. Such a goal is very ambitious, so we shall make three simplifying assumptions:

- The tracking data are noiseless. This gives an advantage to the gun (see Reference i) but is not too significant since optical and millimeter radar systems promise very accurate tracking and also since in many cases the errors from evasive maneuvers far exceed errors resulting from errors in state estimation.
- The target is limited only in the r.m.s. value of the Nth derivative of its path. That is, the class of maneuvers $\overline{\underline{X}}_N$ is limited to those x(t) for which

$$C_N^2 = \lim_{R \to \infty} \frac{1}{2R} \int_{-R}^{R} [x^{(N)}(t)]^2 dt.$$
 1.1

The performance of the fire control is characterized by the r.m.s. prediction error

$$\varepsilon^{2}(x,p) = \lim_{R \to \infty} \frac{1}{2R} \int_{-R}^{R} \left[\hat{x}(t+T,p) - x(t+T) \right]^{2} dt \qquad 1.2$$

where T is the time of flight of the bullet, $p \in P$, P is the class of prediction algorithm such that \hat{x} is the predicted value of x(t+T) given all data on x(t-s) for $s \ge 0$.

The last two assumptions are the closest concession we make to stationarity. The reason for averaging over time in Equation 1.2 is to provide a measure that does not encourage the target to make a one-time maneuver at the time of firing a single round but rather forces the target to avoid rounds fired at unknown times or to avoid bursts of rounds fired over time.

Harry L. Reed, Jr., "Some Bounds on the Generalized Fire Control Problem," Ballistic Research Laboratories Report No. 1946, November 1976 (AD A033043).

Finally, the use of an r.m.s. error gives an incomplete measure of effectiveness for maneuvers with statistics that do not allow an adequate measure of probability of hit from the r.m.s. error (see, for example, Reference 2). However, for optimal maneuvers, the r.m.s. error is a fairly good measure (see Section 5).

We shall omit the subscript N unless its particular value is important. The following is our overall strategy:

Let
$$\varepsilon_0 = \sup_{X \in \overline{X}} \quad \inf_{p \in P} \varepsilon(x,p)$$
 1.3

$$\varepsilon^{\circ} = \inf_{p \in P} \sup_{x \in \underline{X}} \varepsilon(x,p)$$
 1.4

$$\widetilde{\varepsilon}_{o} = \varepsilon(x_{o}, p_{o}) = \sup_{x \in \underline{X}_{G}} \inf_{p \in P} \varepsilon(x, p)$$
 1.5

$$\tilde{\epsilon}^{0} = \sup_{X \in \overline{X}} \epsilon(x, p_{0})$$
 1.6

where $\overline{\underline{X}}_G$ is the class of stationary Gaussian maneuvers that satisfy Equation 1.1 and also satisfy.

$$\int_{-\infty}^{\infty} \frac{|\log |\Phi(w)||}{1+w^2} dw < \infty$$

where $\Phi(w)$ is the power spectral density of the Nth derivative.

Since $\overline{\underline{X}}_G \subseteq \overline{\underline{X}}$ and $\underline{p}_Q \in P$, we have

$$\tilde{\varepsilon}_{0} \leq \varepsilon_{0} \leq \varepsilon^{0} \leq \tilde{\varepsilon}^{0}$$
 1.8

The argument that gives the middle inequality is a consequence of the properties of sup and of inf, is common knowledge in game theory, and is given in Appendix 1 for the benefit of the uninitiated.

We shall show that

$$\tilde{\epsilon}_{0} = \tilde{\epsilon}^{0}$$
 1.9

and thus that

$$\varepsilon_{o} = \varepsilon^{o}$$
. 1.10

²Harry L. Reed, Jr., "Limitations of the R.M.S. Criterion for Fire Control," Ballistic Research Laboratories Report No. 1805, July 1975 (AD A014986).

We shall also evaluate ε_0 for N = 0, 1, and 2 and show how to evaluate it for higher values of N.

Equation 1.10 implies that in a game between two "smart" players, $\mathbf{x}_{_{\mathrm{O}}}$ and $\mathbf{p}_{_{\mathrm{O}}}$ are optimal strategies.

2. LOWER BOUND

For Gaussian maneuvers the optimal predictors are linear operators of the form (see Reference 3)

$$\hat{x}(t+T,p_h) = \sum_{m=0}^{N-1} x^{(m)}(t) \frac{T^m}{m!} + \int_0^\infty h(s)x^{(N)}(t-s)ds$$
 2.1

Integration by parts gives

$$x(t+T) - \hat{x}(t+T, p_h) = \int_0^\infty u_N(T-s)x^{(N)}(t+s)ds - \int_0^\infty h(s)x^{(N)}(t-s)ds$$
2.2

where

$$u_0(t) \approx \delta(t)$$
 2.3

and for N > 0

$$u_N(t) = \frac{t^{N-1}}{(N-1)!}$$
 for $t \ge 0$

$$= 0$$
 for $t < 0$. 2.5

Again we shall use

$$f(t)$$
 for $u_N(T-t)$

and

$$a(t)$$
 for $x^{(N)}(t)$

unless the particular value of N is important to the argument at hand.

Norbert Wiener, Extrapolation, Interpolation, and Smoothing of Stationary Time Series, The Technology Press of M.I.T. and John Wiley & Sons, Inc., New York.

Let

$$\phi(s) = \lim_{R \to \infty} \frac{1}{2R} \int_{-R}^{R} a(t)a(t+s)dt. \qquad 2.6$$

Equations 1.1 and 1.7 allow us to write

$$\phi(s) = \int_{-\infty}^{\infty} \alpha(t)\alpha(t+s)dt$$
 2.7

where

$$\alpha(t) = 0$$
 $t < 0$ 2.8

and of course

$$C^2 = \int_0^\infty [\alpha(t)]^2 dt.$$
 2.9

Using

$$\phi(\mathbf{r}-\mathbf{s}) = \int_{-\infty}^{\infty} \alpha(\mathbf{t}+\mathbf{r})\alpha(\mathbf{t}+\mathbf{s})d\mathbf{t}$$
 2.10

$$= \int_{-\infty}^{\infty} \alpha(t-r)\alpha(t-s)dt \qquad 2.11$$

and

$$\phi(r+s) = \int_{-\infty}^{\infty} \alpha(t-r)\alpha(t+s)dt, \qquad 2.12$$

we can combine Equation 1.2 and 2.2 to write

$$\varepsilon^{2} = \int_{-\infty}^{\infty} dt \left\{ \int_{0}^{\infty} [f(s)\alpha(t+s) - h(s)\alpha(t-s)] ds \right\}^{2}$$

$$= \int_{0}^{\infty} dt \left\{ \int_{0}^{\infty} [f(s)\alpha(t+s) - h(s)\alpha(t-s)] ds \right\}^{2}$$

$$+ \int_{-\infty}^{0} dt \left\{ \int_{0}^{\infty} f(s)\alpha(t+s) ds \right\}^{2}.$$
2.14

To minimize with respect to p, we pick h to satisfy

$$\int_{0}^{\infty} f(s)\alpha(t+s)ds = \int_{0}^{\infty} h(s)\alpha(t-s)ds$$
 2.15

which puts the first term of the function in Equation 2.14 equal to zero.

To maximize with respect to x, we then pick α to maximize

$$\varepsilon^{2} = \int_{\infty}^{0} dt \left\{ \int_{0}^{\infty} f(s)\alpha(t+s)ds \right\}^{2}$$

$$= \int_{0}^{\infty} dt \left\{ \int_{0}^{\infty} f(s)\alpha(s-t)ds \right\}^{2}$$

$$= \int_{0}^{\infty} dt \left\{ \int_{0}^{\infty} f(s+t)\alpha(s)ds \right\}^{2}.$$
2.16

To do this, we set

$$\delta \varepsilon^2 = 2 \int_0^\infty dt \int_0^\infty f(s+t)\alpha(s)ds \int_0^\infty f(r+t)\delta\alpha(r)dr = 0$$
 2.17

subject to

$$\int_0^\infty \alpha(\mathbf{r}) \ \delta\alpha(\mathbf{r}) = 0.$$
 2.18

Therefore

$$\alpha(r) = k \int_0^{\infty} dt \int_0^{\infty} f(r+t) f(s+t)\alpha(s)ds.$$
 2.19

Multiplying Equation 2.19 by $\alpha(r)$ and integrating, we have

$$\varepsilon^2 = \frac{C^2}{k}$$
 2.20

which shows that $k \ge 0$. Further

$$\varepsilon_0^2 = \frac{C^2}{k_0}$$

where k_{0} is the least eigenvalue of Equations 2.9 and 2.19.

In Section 4 we show how this eigenvalue problem is related to an eigenvalue problem for a system of differential equations and we evaluate k_0 for N = 0, 1, and 2.

3. UPPER BOUND

Even though the class \overline{X} is only constrained by

$$C^2 = \lim_{R \to \infty} \frac{1}{2R} \int_{-R}^{R} [a(t)]^2 dt$$

we can define

$$\phi(s) = \lim_{R \to \infty} \frac{1}{2R} \int_{-R}^{R} a(t)a(t+s)dt$$
 3.1

and know that

$$\Phi(w) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \phi(s) e^{-iws} ds \ge 0.$$
 3.2

Now we shall use the predicter which was defined in the previous section by Equation 2.15 for the particular $\alpha(r)$ given in Equation 2.19. Then Equations 1.7, 2.2, and 3.1 give (for any x)

$$\varepsilon^{2}(x,p_{o}) \approx \int_{0}^{\infty} dr \int_{0}^{\infty} ds \left\{ f(s)f(r)\phi(r-s) - 2 f(s)h(r)\phi(r+s) + h(r)h(s)\phi(r-s) \right\}.$$

Using

$$\phi(\mathbf{r}) = \int_{-\infty}^{\infty} \Phi(\mathbf{w}) e^{i\mathbf{w}\mathbf{r}} d\mathbf{w}, \qquad 3.4$$

we can derive

$$\varepsilon^{2}(x,p_{0}) = \int_{-\infty}^{\infty} |\overline{F}(w) - H(w)|^{2} \Phi(w) dw \qquad 3.5$$

where

$$H(w) = \int_0^\infty h(t) e^{-iwt} dt$$
 3.6

and

$$F(w) = \int_{0}^{\infty} f(t) e^{-iwt} dt$$
 3.7

We shall show that

$$|\overline{F}(w) - H(w)|^2 = \frac{1}{k_0}$$
 3.8

and thus that

$$\varepsilon^{2}(x,p_{o}) = \frac{1}{k_{o}} \int_{-\infty}^{\infty} \Phi(w) dw = \frac{C^{2}}{k_{o}}$$
 3.9

for all $x \in \overline{X}$.

To do that, we first take the Fourier transform of Equation 2.15 to get

$$\int_0^\infty e^{-iwt} dt \int_0^\infty f(s)\alpha(t+s)ds = H(w)A(w)$$
 3.10

where

$$A(w) = \int_0^\infty \alpha(t) e^{-iwt} dt$$
 3.11

Some manipulation of the left hand side of Equation 3.10 gives

$$\int_{0}^{\infty} e^{-iwt} dt \int_{0}^{\infty} f(s)\alpha(t+s)ds$$

$$= \int_{-\infty}^{\infty} e^{-iwt} dt \int_{0}^{\infty} f(s)\alpha(t+s)ds - \int_{-\infty}^{0} e^{-iwt} dt \int_{0}^{\infty} f(s)\alpha(t+s)ds$$

$$= \overline{F}(w)A(w) - \int_{0}^{\infty} e^{iwt} \int_{0}^{\infty} f(s)\alpha(s-t)ds$$

$$= \overline{F}(w)A(w) - \int_{0}^{\infty} e^{iwt} \int_{0}^{\infty} f(t+r)\alpha(r)dr$$
3.12

Therefore

$$|\overline{F}(w) - H(W)|^2 = |B(w)/A(w)|^2$$
 3.13

where

$$B(w) = \int_{-\infty}^{\infty} e^{iwt} \beta(t) dt$$
 3.14

$$\beta(t) = \int_0^\infty f(t+r)\alpha(r)rt \quad t \ge 0$$

$$= 0 \qquad t < 0$$

We then have

$$|B(w)|^2 = B(w)\overline{B}(w) = \int_{-\infty}^{\infty} e^{iwp} dp \int_{0}^{\infty} \beta(q)\beta(p+q)dq$$
 3.16

Note that this convolution is an even function of p so that

$$|B(w)|^2 = \int_{-\infty}^{\infty} e^{iwp} dp \int_{0}^{\infty} \beta(q) \beta(|p|+q) dq$$
 3.17

Now using Equation 2.19, we have

$$\int_{0}^{\infty} \beta(q) \beta(|p|+q) dq = \int_{0}^{\infty} dq \int_{0}^{\infty} f(q+r) \alpha(r) dr$$

$$\times \int_{0}^{\infty} f(q+|p|+s) \alpha(s) ds$$

$$= \frac{1}{k_{0}} \int_{0}^{\infty} \alpha(|p|+s) \alpha(s) ds$$
3.18

and finally

$$|B(w)\overline{B}(w)| = \frac{1}{k_0} \int_{-\infty}^{\infty} e^{iwp} dp \int_{0}^{\infty} \alpha(|p|+s)\alpha(s) ds$$

$$= \frac{1}{k_0} |A(w)\overline{A}(w)|$$
3.19

and we have from Equation 3.13 and 3.5 that

$$\varepsilon^2(x,p_0) = \frac{C^2}{k_0}$$

as advertised in Equation 3.9.

Another approach to Equation 3.8 is to show that

$$B(w) = \frac{1}{\sqrt{k_0}} \overline{A}(w)$$
 3.20

which can be shown by showing that

$$\beta(t) = \frac{1}{\sqrt{k_0}} \alpha(t). \qquad 3.21$$

To do this, we combine Equation 2.19 and 3.15 to get

$$\beta(t) = \int_0^\infty f(t+r)dr \int_0^\infty k_0 dq \int_0^\infty f(r+q)f(s+q)\alpha(s)ds$$

$$= k_0 \int_0^\infty f(t+r)dr \int_0^\infty f(r+q)\beta(q)dq$$
3.22

Thus $\beta(t)$ satisfies the same integral equation as $\alpha(t)$. In the next section we relate this integral equation to the eigenvalue problem for a differential equation. This eigenvalue problem has only one linearly independent solution (see Appendix 2) and so we can write

$$\beta(t) = \gamma \alpha(t) \qquad 3.23$$

Then

$$\int_0^\infty [\beta(t)]^2 dt = \gamma^2 \int_0^\infty [\alpha(t)]^2 dt$$
 3.24

which gives

$$\int_0^\infty \left\{ \int_0^\infty f(t+r)\alpha(r)dr \right\}^2 dt = \gamma^2 \int_0^\infty [\alpha(t)]^2 dt$$
 3.25

using the definition of $\beta(t)$ and which can be rewritten as

$$\int_{0}^{\infty} \alpha(r) dr \int_{0}^{\infty} f(t+r) dt \int_{0}^{\infty} f(t+s) \alpha(s) ds$$

$$= \gamma^{2} \int_{0}^{\infty} [\alpha(t)]^{2} dt$$
3.26

and finally (from Equation 2.19)

$$\frac{1}{k_0} \int_0^\infty [\alpha(r)]^2 dr = \gamma^2 \int_0^\infty [\alpha(t)]^2 dt$$
 3.27

which gives

$$\gamma = \frac{1}{\sqrt{k_0}}$$
 3.28

4. THE EIGENVALUE PROBLEM

We have

$$\int_0^\infty \alpha^2(\mathbf{r}) = C^2$$
 4.1

and

$$\alpha(r) = k_{o} \int_{o}^{\infty} dt \int_{o}^{\infty} u(T-r-t)u(T-s-t)\alpha(s)ds$$

$$= k_{o} \int_{o}^{T-r} dt \int_{o}^{T-t} \frac{(T-r-t)^{N-1}}{(N-1)!} \frac{(T-s-t)^{N-1}}{(N-1)!} \alpha(s)ds$$
4.2

for $r \leq T$.

We also have $\mathbf{k}_{_{\mbox{\scriptsize 0}}} > 0 \,,$ and $\mathbf{k}_{_{\mbox{\scriptsize 0}}}$ is the least eigenvalue of this system of equations.

If r > T

$$u(T-r-t) = 0$$
 since $t \ge 0$

and thus

$$\alpha(r) = 0 \quad \text{for} \quad r > T \qquad 4.3$$

If N = 0

$$u(r) = \delta(r)$$

and

$$\alpha(\mathbf{r}) = k_0 \int_0^\infty d\mathbf{r} \int_0^\infty \delta(\mathbf{T} - \mathbf{r} - \mathbf{t}) \, \delta(\mathbf{T} - \mathbf{s} - \mathbf{t}) \, \alpha(\mathbf{s}) \, d\mathbf{s}$$
$$= k_0 \, \alpha(\mathbf{r})$$

So for N = 0

$$k_0 = 1$$
 4.4

and

$$\varepsilon_{Q} = C$$
 4.5

Let N \geq 1. We can differentiate Equation 4.2 to get for 0 \leq t \leq T

$$\alpha^{(2N)} = (-1)^N k_0 \alpha \qquad 4.6$$

$$\alpha^{(M)}(T) = 0$$
 for M=0 to N-1 4.7

$$\alpha^{(M)}(0) = 0$$
 for M=N to 2N-1 4.8

The uniqueness of the solution to this system of equations is shown in Appendix 2.

Now let N=1

$$\ddot{a} = -k_0 \alpha$$

$$\dot{\alpha}(0) = \alpha(T) = 0$$

$$\alpha = \sqrt{2/T} C \cos \left(\frac{\pi}{2T} t\right)$$
 4.9

$$k_{o} = \left(\frac{\pi}{2T}\right)^{2}$$
 4.10

$$\varepsilon_{\rm O} = \frac{2}{\Pi} \, \rm CT$$
 4.11

Finally let N = 2

$$\alpha = k_0 \alpha$$

$$\ddot{\alpha}$$
 (o) = $\ddot{\alpha}$ (o) = $\dot{\alpha}$ (T) = α (T) = 0

(The classical problem of the vibration of a clamped rod.) Letting k_0 = $\lambda_0^{\ 4}$, we have

$$1 + \cosh \left(\lambda_0^{T}\right) \cos \left(\lambda_0^{T}\right) = 0$$
 4.12

$$\lambda_0^T \cong 1.875$$

$$\alpha = \frac{C}{\sqrt{T}} \begin{cases} \frac{\cosh[\lambda_0(t-T/2)]}{\cosh[\lambda_0T/2]} \end{cases}$$
 4.13

$$-\frac{\sin[\lambda_{o}(t-T/2)]}{\sin[\lambda_{o}T/2]}$$

$$\varepsilon_{O} = \frac{2}{\left(\lambda_{O}T\right)^{2}} \left(\frac{1}{2} CT^{2}\right)$$
 4.14

$$\simeq$$
 .569 $\left(\frac{1}{2} \text{ CT}^2\right)$ 4.15

THE GENERAL PROBLEM

In this section we shall see how far we can go using hit probability rather than the r.m.s. criterion. In doing this, we shall have to give up the neatness of finding an exact answer. On the other hand, we shall find bounds on the problem, and these bounds will be shown to bracket the problem closely enough for many "first analyses."

Let us discuss the problem where x(t) has a single spatial dimension. Associated with a class of maneuvers is a probability distribution function

$$u\{x(t+T) - \hat{x}(t+T,p) \mid x(t-s), s \ge 0\}.$$
 5.1

That is, u is the distribution of the error between the future position and the predicted future position given the past. Let y be this error in future position. We can average over time to find a distribution function

$$u(y | x,p)$$
. 5.2

The probability of hit q is

$$q(x,p) = \int_{-\ell/2}^{\ell/2} du(\xi \mid x,p),$$
 5.3

where ℓ is the size of the target. The pilot wishes to keep q small. His goal might be

$$q^{0} = \inf_{X \in X} \sup_{p \in P} q(x,p).$$
 5.4

Likewise, the gunner might try for

$$q_0 = \sup_{p \in P} \inf_{x \in X} q(x,p).$$
 5.5

The set \overline{X} , the set P, the set X_G , the maneuver \overline{X}_O , the prediction algorithm P_O , and the error ϵ_O are as defined in Section 1.

We can define
$$\widetilde{q}^{o} = \widetilde{q}^{o}(\widetilde{\epsilon}_{o}/\ell) = q(x_{o}, p_{o}) = \frac{1}{\sqrt{2\pi}} \sum_{\epsilon=0}^{\infty} \int_{-\ell/2}^{\ell/2} e^{-\xi^{2}/(2\widetilde{\epsilon}_{o}^{2})} d\xi \qquad 5.6$$

Since x is Gaussian, p maximizes the hit probability as well as it minimizes the error. Thus

$$q^{\circ} \leq \widetilde{q}^{\circ}$$
. 5.7

We can also define

$$\widetilde{q}_{o} = \inf_{X} q(x, \widetilde{p}_{o})$$
, 5.8

where \widetilde{p}_0 is a variant of the algorithm p_0 and will be described in Section 6.

As usual, we have

$$\widetilde{q}_0 \le q_0 \le q^0 \le \widetilde{q}^0$$
, 5.9

but this time we have not been able to collapse this chain of inequalities. In fact we are only able to find a lower bound $z(\widetilde{\epsilon}/\ell)$ such that

$$z \le \widetilde{q}_0 \le q_0 \le q^0 \le \widetilde{q}^0$$
. 5.10

Nevertheless, these bounds may well still be useful for first estimates since they provide a variation of no more than 70 percent. A tabulation of the lower bound z and the upper bound \mathfrak{q}° and their ratio is given in Table 1.

6. THE ALGORITHM
$$\widetilde{P}_{0}$$

Define the algorithm \widetilde{p}_{0} to be

$$\hat{x}(t+T,\tilde{p}_{0}) = y_{0} + \hat{x}(t+T,p_{0}).$$
 6.1

Then

$$u(y | x, \widetilde{p}_0) = u(y - y_0 | x, p_0)$$
. 6.2

The value y_0 is the value that maximizes

$$q(y_0, x, p_0) = \int_{y=-\ell/2}^{y=\ell/2} du(y - y_0) | x, p_0)$$
 6.3

From Appendix C we have

Table 1

ε	$\widetilde{q}^{o}(\epsilon)$	\tilde{q}^{o}/z
∞	.000	1.382
5.557	.072	1.434
2.669	.149	1.486
1.721	.229	1.524
1.225	.317	1.585
. 935	.407	1.628
.775	.481	1.605
.622	.578	1.652
.548	.639	1.597
.461	.722	1.604
.354	.843	1.685
.335	.864	1.571
.316	.886	1.477
. 296	.909	1.399
.274	.932	1.332
.250	.954	1.273
.224	.975	1.218
.194	.990	1.165
.158	.998	1.109
.112	1.000	1.053
.000	1.000	1.000
	5.557 2.669 1.721 1.225 .935 .775 .622 .548 .461 .354 .335 .316 .296 .274 .250 .224 .194 .158 .112	 ∞ .000 5.557 .072 2.669 .149 1.721 .229 1.225 .317 .935 .407 .775 .481 .622 .578 .548 .639 .461 .722 .354 .843 .335 .864 .316 .886 .296 .909 .274 .932 .250 .954 .224 .975 .194 .990 .158 .998 .112 1.000

$$q(x, \widetilde{p}_0) = \sup_{y_0} q(y_0, x, p_0) \ge z(\sigma/\ell) \ge z(\widetilde{\epsilon}_0/\ell)$$
 6.4

where σ is the standard deviation around the mean. The last inequality follows since z is a monotonically decreasing function and since σ minimizes the r.m.s. error.

Since the middle inequality in Equation 6.4 holds for all x, we have

$$\widetilde{q}_{o} \ge z(\widetilde{\varepsilon}_{o}/\ell)$$
. 6.5

7. CONCLUSIONS

With respect to the r.m.s. criterion and the r.m.s. bound on an Nth derivative, the duel between a gunner and a target is a game with a saddle point which can be precisely defined and hence stable strategies exist for both players.

If hit probability is used as the criterion, we have been unable to define a saddle point precisely. However, we can find bounds that show that the difference between the performance for such a saddle point and the saddle point for the r.m.s. case may well be small enough to use the r.m.s. criterion as a good "first analysis."

APPENDIX A

First consider $\boldsymbol{\epsilon}_{_{\textstyle O}}.$ We note that for each $\delta \geqslant 0$ there exists an $\boldsymbol{x}_{_{\textstyle \delta}}$ such that

$$\inf_{p} \epsilon(x_{\delta}, p) \geq \epsilon_{0} - \delta$$

which follows from the definition of sup.

Thus

$$\varepsilon(x_{\delta},p) \geq \varepsilon_{0} - \delta$$

for all p which follows from the definition of inf.

Likewise, there exists a \boldsymbol{p}_{δ} such that

$$\varepsilon(x,p_{\delta}) \leq \varepsilon^{0} + \delta$$

for all x.

Thus

$$\varepsilon_{o} - \delta \le f(x_{\delta} p_{\delta}) \le \varepsilon^{o} + \delta$$

for all δ and thus

$$\epsilon_0 \le \epsilon^0$$
.

APPENDIX B*

Statement of Problem.

Let k > 0 be such that the differential equation

$$x^{(2n)} = (-1)^n kx$$

 $x^{(m)}(T) = 0 (m=0,1,...,n-1)$
 $x^{(m)}(0) = 0 (m=n,n+1,...,2n-1)$

has a nontrivial solution. Prove that this solution is unique up to constant multiples.

Proof.

The proof consists in showing that for any two nontrivial solutions x and y the equality sign in Schwarz's inequality

$$\left(\int_{0}^{T} xy \, dt\right)^{2} \leq \int_{0}^{T} x^{2} dt \int_{0}^{T} y^{2} dt$$

holds, which occurs if and only if y = cx, c a constant.

To this end, we note first that

$$\int_{0}^{T} xy \ dt = \frac{1}{k} \int_{0}^{T} x^{(n)} y^{(n)} dt.$$
 (B-1)

This follows from

^{*}The analysis in this appendix was provided by Mr. Walter O. Egerland of the Ballistic Modeling Division, Ballistic Research Laboratory.

$$\int_{0}^{T} xy \, dt = \frac{(-1)^{n}}{k} \int_{0}^{T} x^{(2n)}y \, dt$$

$$= \frac{(-1)^{n}}{k} \left\{ yx^{(2n-1)} \Big|_{0}^{T} - \int_{0}^{T} x^{(2n-1)}y' dt \right\}$$

$$= \frac{(-1)^{n+1}}{k} \int_{0}^{T} x^{(2n-1)}y' dt$$

$$= \frac{(-1)^{n+j}}{k} \int_{0}^{T} x^{(2n-j)}y^{j} dt, j=1,2,...n \quad (B-2)$$

Next, we write the identify

$$xy = x(0)y(0) + \int_0^t (x'y + xy')dt,$$

and find successively

$$xy = x(0)y(0) + \frac{(-1)^n}{k} \int_0^t (x'y^{(2n)} + y'x^{(2n)}) dt$$

$$= x(0)y(0) + \frac{(-1)^n}{k} \left\{ y^{(2n-1)}x' + x^{(2n-1)}y' - \int_0^t (y^{(2n-1)}x'' + x^{(2n-1)}y'') dt \right\}$$

$$= \vdots$$

$$= x(0)y(0) + \frac{(-1)^n}{k} \left[\sum_{j=1}^{n-1} (-1)^{j+1} \right\} y^{(2n-j)}x^j + x^{(2n-j)}y^j + (-1)^{n+1} x^{(n)} y^{(n)}$$

Integration over the interval [0,T], using (B-1) and (B-2), yields

$$\int_0^T xy \ dt = x(0)y(0)T - (2n-1)\int_0^T xy \ dt$$
or
$$\int_0^T xy \ dt = \frac{x(0)y(0)}{2n} T. \qquad (B-3)$$
In particular,
$$\int_0^T x^2 dt = \frac{x(0)^2}{2n} T$$
and
$$\int_0^T y^2 dt = \frac{y(0)^2}{2n} T.$$

Hence, equality in Schwarz's inequality holds, and the proof is complete.

APPENDIX C

Let $u(\xi)$ be any distribution function which we will take for convenience as having zero mean. Then

$$\sigma^2 = \int_{-\infty}^{\infty} \xi^2 du(\xi). \tag{C-1}$$

We want to relate o with

$$q = \sup_{y} \int_{y-\ell/2}^{y+\ell/2} du$$
 (C-2)

It is convenient to find a function such that

$$\sigma \ge r(q)$$
. (C-3)

This function is monotonically decreasing with ${\bf q}$ and thus we can use it to define

$$q \ge z(\sigma)$$
. (C-4)

implicitly.

We can write

$$\sigma^2 = \sum_{m=-\infty}^{\infty} \int_{m \ell/2}^{(m+1)\ell/2} \xi^2 du(\xi)$$

$$\sigma^{2} \ge \sum_{m=0}^{\infty} \left(\frac{m\ell}{2}\right)^{2} \int_{m\ell/2}^{(m+1)\ell/2} du + \sum_{m=-\infty}^{-1} \left(\frac{m+1}{2}\right)^{2} \int_{m\ell/2}^{(m+1)\ell/2} du$$

$$\sigma^{2} \geqslant \sum_{m=0}^{\infty} \left(\frac{m\ell}{2}\right)^{2} \mu_{m} + \sum_{m=-\infty}^{-1} \left[\frac{(m+1)\ell}{2}\right]^{2} \mu_{m}$$
 (C-5)

where

$$\mu_{\rm m} = \int_{\rm m0/2}^{\rm (m+1) \, l/2} du \ge 0$$

and

$$\mu_{m} + \mu_{m+1} \leq q$$

and

$$\sum_{m=-\infty}^{\infty} \mu_m = 1 .$$

If we write

$$v_{m} = \mu_{m} + \mu_{(-1-m)},$$

we have "

$$\sigma^2 \ge \Sigma = \sum_{m=0}^{\infty} \frac{m\ell}{2}^2 v_m, \qquad (C-6)$$

where

$$0 \le v_0 \le q , \qquad (C-7)$$

$$0 \le v_{m} + v_{m+1} \le 2q$$
, (C-8)

$$\sum_{m=0}^{\infty} v_m = 1. \tag{C-9}$$

It is not hard to show that we have a lower bound for Σ defined in Equation C-6 if we let

$$v_{\rm m} = q$$
 for m=0, M-1, (C-10)

$$v_{M} = 1 - Mq,$$
 (C-11)

$$v_{\rm m} = 0$$
 for $m > M$, (C-12)

where

$$M = greatest integer [1/q].$$
 (C-13)

The proof of this goes as follows:

- (i) If $v_0 = q$, go to step (iv)
- (ii) If $v_0 < q$ and $v_0 + v_1 = b \ge q$, put $v_0 = q$ and $v_1 = b q$. This will decrease Σ . Then go to step (iv).

- (iii) If $v_0 + v_1 = b < q$, put $v_0 = b$, $v_1 = 0$ and reduce and other v_m 's to make $v_0 = q$. This again will decrease Σ . Then go to step (iv).
- (iv) Now work on v_1 and v_2 as we worked on v_0 and v_1 .
- (v) Continue on with v_2 and v_3 , etc.

We then have

$$\sigma^2/\ell^2 \ge \sum_{m=0}^{M-1} \frac{m^2 q}{4} + \frac{M^2}{4} [1 - Mq],$$
 (C-14)

which we can write in closed form as

$$\sigma^2/\ell^2 = r(q) = \frac{(M-1)M(2M-1)}{24} q + \frac{M^2}{4} [1 - Mq].$$
 (C-15)

We now need only show that this function is monotonically decreasing for $0 < q \le 1$, and we have implicitly defined $z(\sigma)$.

First let $q = \frac{1}{M}$. Then

$$r(q) = \frac{(M-1)(2M-1)}{24}$$

which increases as q decreases.

We can write Equation C-14 as

$$r(q) = \frac{M^2}{4} + qM \left[\frac{-4M^2 - 3M + 1}{24} \right]$$
 (C-16)

For $\frac{1}{M+1} < q \le \frac{1}{M}$, M is fixed in Equation C-16 and r(q) varies only as a constant times q. Since

$$-4M^2 - 3M + 1 < 0$$
 for $q \le 1$,

we have that r(q) increases as q decreases from $\frac{1}{M}$ to $\frac{1}{M+1}$.

We should point out that $r(\cdot)$ is not actually achievable by a $u(\cdot)$. In particular, there is a jump of q at zero and a jump of q/2 at $\ell/2$ so the interval $(-\ell/4, 3\ell/4)$ would have measure 3q/2. Thus z is only a lower bound.

DISTRIBUTION LIST

1017 2131
o. of opies <u>Organization</u>
Director US Army Air Mobility Research and Development Laboratory Ames Research Center Moffett Field, CA 94035
1 Commander US Army Electronics Research and Development Command Technical Support Activity ATTN: DELSD-L Fort Monmouth, NJ 07703
1 Commander US Army Communications Research
and Development Command ATTN: DRDCO-SGS Fort Monmouth, NJ 07703
<pre>1 Commander US Army Missile Research and Development Command ATTN: DRDMI-R</pre>
Redstone Arsenal, AL 35809 1 Commander US Army Missile Materiel Readiness Command ATTN: DRSMI-AOM Redstone Arsenal, AL 35809
1 Commander US Army Tank Automotive Research and Development Command ATTN: DRDTA-UL Warren, MI 48090
5 Commander US Army Armament Research and Development Command ATTN: DRDAR-TSS (2 cys) DRDAR-TD, Dr. R. Weigle DRDAR-TDS, Mr. V. Lindner DRDAR-SCF Dover, NJ 07801

DISTRIBUTION LIST

No. of		No. of	
Copies	Organization	Copies	Organization
_	Commander US Army Armament Materiel Readiness Command ATTN: DRSAR-LEP-L, Tech Lib Rock Island, IL 61299	1	Deputy Under Secretary of the Army (Operations Research) Washington, DC 20310 Commandant US Military Academy
2	Commander White Sands Missile Range ATTN: STEWS-TE-ML STEWS-NR-PA		ATTN: COL John L. Palmer Dept. of Engineering West Point, NY 10996
1	White Sands, NM 88002 Commander	1	Commander Naval Ordnance Systems Command Washington, DC 20360
	US Army Training and Doctrine Command ATTN: ATCD-FT Fort Monroe, VA 23651	1	Commander Office of Naval Research ATTN: Mr. S. M. Selig 800 North Quincy Street
1	Director US Army TRADOC Systems Analysis Activity ATTN: ATAA-SL, Tech Lib White Sands Missile Range NM 88002	1	Arlington, VA 22217 Director Special Projects Office Department of the Navy Washington, DC 20360
1	Commander US Army Aviation Center ATTN: ATZK-D-MT Fort Rucker, AL 36360	1	Commander Naval Weapons Center ATTN: Code 753 China Lake, CA 93557
1	US Army Combined Arms Combat Developments Activity ATTN: ATCACC-CA		AF/XOOFA Washington, DC 20330 AF/SAV
1	Fort Leavenworth, KS 66027 Commander MASSTER ATTN: ATMAS-OEP-Q Fort Hood, TX 76544		Washington, DC 20330 AFSC (DOVS) Andrews AFB Washington, DC 20331
1	Commander Operational Test and Evaluation		TAWC/OA (Mr. J. Durrenberger) Eglin AFB, FL 32542
	Agency ATTN: FDTE-PO-OB 5600 Columbia Pike Falls Church, VA 22041		AFWL (SA) Kirtland AFB, NM 87117

DISTRIBUTION LIST

No. of Copies Organization

United States Air Force Academy Department of Astronautics and Computer Science ATTN: DFACS/LTC E. J. Bauman Colorado 80840

Martin Marietta
ATTN: Dr. Joseph Sternberg
6801 Rockledge Drive
Bethesda, MD 20034

Aberdeen Proving Ground

Dir, USAMSAA

ATTN: Dr. J. Sperrazza

Mr. D. O'Neill

Mr. H. Burke

Cdr, USATECOM

ATTN: DRSTE-SG-H

DRSTE-SE

DRSTE-SY, J. Marley

DRSTE-AD

Dir, USAMTD

ATTN: STEAP-MT-M